Predicting house mouse outbreaks in the wheat-growing areas of south-eastern Australia

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Abstract. Outbreaks of house mice (Mus domesticus) occur irregularly in the wheat-growing areas of south-eastern Australia and impact on agricultural production. Prediction of mouse outbreaks has been successful in the central mallee region of Victoria and we have attempted to extend this prediction to a wider region of Victoria and South Australia. We developed two models: (1) a qualitative outbreak prediction from winter and spring rainfall and (2) a quantitative prediction of maximum autumn density of mice from winter and spring rainfall and spring mouse abundance. Both models have achieved some success at prediction. For the qualitative model we can achieve 70% correct predictions from winter and spring rainfall. The quantitative model is less satisfactory, and although it gives some predictability of high autumn densities, it misses too often the severe outbreaks that cause most damage. We highlight the demographic problems that need further analysis to increase our predictive abilities for mouse outbreaks.

Introduction

House mouse outbreaks are an undesirable feature of the wheat-growing regions of south-eastern Australia. Detailed studies of local populations have been carried out at different sites for more than 40 years, and these studies provide a wealth of demographic data for understanding the causes of these outbreaks (Newsome 1969a, b; Redhead and Singleton 1988; Mutze 1989, 1991; Singleton 1989; Singleton and Redhead 1990; Boonstra and Redhead 1994; Pech et al. 1999; Singleton et al. 2001). If one understands the mechanisms behind demographic changes, the next step is to construct models to predict outbreaks. For the house mouse in south-eastern Australia, a detailed modelling effort was undertaken by Pech et al. (1999), concentrating on the data available from one site in the central mallee region of Victoria. The Pech model has been quite successful in predicting changes in mouse numbers in the central mallee, and the objective of this paper is to try to extend this modelling effort to a broader spatial scale. In particular, we ask this question: Can we achieve a predictive model of house mouse plagues that can be used throughout the mallee region of Victoria and South Australia both to assist farmers and to add to our understanding of the ecology of mouse plagues?

Materials and methods

Quantitative house mouse data were available from two main sites: Walpeup in the Victorian mallee (G.R. Singleton, unpublished data) from 1983 to 2002 and Roseworthy in South Australia from 1979 to 2001 (G. Mutze, unpublished data). In addition, quantitative data were available from four other sites in Victoria and South Australia from 1998 to 2002 (Figure 1). Longworth and Elliott live-traps were set in crops (typically 6 × 6 grids, 10 m spacing) and along fence lines (10 m spacing). Mouse abundance was estimated by adjusted trap success, and the general methods are described more completely in Mutze (1991) and Singleton et al. (2001).

Qualitative house mouse data were dichotomised at 0 = no outbreak, 1 = outbreak. These qualitative data were gathered from Saunders and Giles (1977), Mutze (1989), and Singleton and Redhead (1989), and during the last 20 years from direct reporting from farmers and state agricultural scientists. We have used qualitative mouse data from the nine statistical local areas shown in Figure 1 for 1960–2001. Not all areas have data for each year, but there are many more qualitative data available from a larger area than there are quantitative data.

The schematic model for house mouse outbreaks is shown in Figure 2, and is based on the assumption that food supplies drive changes in density. Mutze et al. (1990) and Pech et al. (1999) used wheat yield as a surrogate measure of food supplies, and we have followed their lead in this
paper. Wheat yield data from the period 1960 to 2001 were obtained from the Australian Bureau of Statistics for the statistical local areas shown in Figure 1. Monthly rainfall data for the same time period were obtained from the Australian Bureau of Meteorology for sites in or near the areas shown in Figure 1. In a few cases for which rainfall data were missing from one station, we used a nearby station for that time period. In general, monthly rainfall data are highly correlated for nearby sites. In addition to temperature and rainfall, we have computed two weather variables to add in the analysis—actual evapotranspiration and soil water deficit. Actual evapotranspiration (AET) is a complex function of temperature and rainfall in association with potential soil water storage. Soil water deficit measures the shortage of water in the soil, and is maximal under drought conditions. Monthly actual and potential evapotranspiration were calculated for all the rainfall stations from temperature and rainfall data. We used the methods of Thornthwaite and

![Figure 1](image1.png)

**Figure 1.** Location of the study areas utilised in this analysis. The nine statistical local areas from which wheat production and qualitative mouse outbreak data were obtained are outlined. The meteorological sites from which rainfall and temperature data were obtained are indicated by a ▼ for each study area. The major long-term study sites of Roseworthy and Waipapa are shown. Quantitative data from 1998–2002 was also obtained from four sites at Loxton, Lameroo, Yarriambiack, and Cararp.

![Figure 2](image2.png)

**Figure 2.** Schematic illustration of the current model for house mouse population dynamics in the grain-growing regions of south-eastern Australia. Food supply is the central variable, but the roles of predation, disease, and social interactions are not clearly understood with respect to how they can modify the basic food-density relationship.
Mather (1957) to estimate actual and potential evapotranspiration and soil water deficit for the areas shown in Figure 1. These estimates agreed with the general maps published by Wang (2001).

These biophysical data were used in logistic regression to estimate the probability of an outbreak for all sites and years for which we had data since 1960 (n = 255 site-years). This approach is similar to that used by Mutze et al. (1990). For sites and years in which we had quantitative data, we used robust multiple regression to attempt to predict the maximum autumn mouse density for that year. The models developed by Pech et al. (1999) and Pech et al. (2001) are based on predicting the rate of increase of mice, so that knowing the starting density of mice and some measure of food resources, one could predict the rate of increase and hence the abundance for the next time step (122 days in the 2001 model). We have adopted a different statistical approach in trying to predict the much simpler qualitative outcome of whether or not there will be an outbreak, and the more difficult quantitative prediction of how large the population will be in autumn, on the assumption that higher abundance in autumn translates into higher crop damage (Caughley et al. 1994).

All statistical analyses were carried out with NCSS 2001 (Number Cruncher Statistical System, Kaysville, Utah, <www.ncss.com>).

Results and discussion

We present our results as a series of questions with relevant data.

Can we achieve a good qualitative prediction of mouse outbreaks?

We used logistic regression to predict the probability of a mouse outbreak using 255 annual observations over the 9 sites. The best predictors were November rainfall and May to September rainfall, and the resulting logistic regression was as in equation (1) below, in which rain is in mm. The resulting logit can be converted to a probability by equation (2).

Classification of the 255 observations was correct 70% of the time (Table 1). We explored many possible alternative predictive models. Adding December rainfall to the above model did not improve predictability. Adding wheat yield to the regression improved predictability but by 3% only. Using wheat yield alone we could predict with 67% accuracy, slightly less than with rainfall alone. Soil water deficit and actual evapotranspiration were of no use in improving predictability. We conclude that the above logistic model based on rainfall is the most useful one at present for predicting qualitatively the chances of a mouse outbreak.

Can we achieve a good quantitative prediction of mouse outbreaks?

We used multiple regression to try to predict the maximum abundance of house mice in autumn from sites with detailed data on mouse abundance. A total of 43 site-years were available, most from the two sites of Walpeup and Roseworthy. The best variables for prediction were December rainfall, April to October rainfall, and September mouse abundance (indexed by adjusted trap success). Equation (3) was obtained, in which rain is in mm and mouse abundance is measured in adjusted trap success. This model, although highly statistically significant, gives an average absolute residual error of 26% in trap success, and is particularly poor in predicting the very highest mouse abundances observed. It is most sensitive to September abundance estimates.

Table 1. Classification table for the prediction of house mouse outbreaks in the Victorian and South Australian mallee regions from the logistic regression given in the text for 1960 to 2001. Boldface items indicate mistakes in classification. Outbreaks are classified qualitatively on the basis of moderate or severe damage to crops

<table>
<thead>
<tr>
<th>Actual event</th>
<th>Estimated from model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>No outbreak</td>
</tr>
<tr>
<td>No outbreak</td>
<td>149</td>
</tr>
<tr>
<td>Outbreak</td>
<td>14</td>
</tr>
<tr>
<td>Total</td>
<td>163</td>
</tr>
</tbody>
</table>

Equations:

Logit(Y) = 2.7325 + 0.0277 (November rain) – 0.00780 (May to September rain)

Prob(outbreak) = 1/[1 + e^log(Y)]

Maximum autumn abundance = –27.158 + 0.5308 (December rain) + 0.1468 (April to October rain) + 1.183 (September trap)
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A tentative model may be more useful for developing understanding and could become useful in practice if a simple way of estimating September mouse abundance can be developed.

Future work should involve a more detailed comparison of the relative predictive abilities of the Pech 1999 model, these two models of house mouse dynamics and that of Mutze et al. (1990). We need to explore what determines the start of the spring breeding season, which is highly variable in house mice. Insects and grass seeds are major components of spring diet (Tann et al. 1991) and the start of breeding could be examined with simple models that predict the onset of insect activity and grass seed production in response to preceding weather patterns. It is clear that rainfall is indeed the driver of mouse outbreaks, as shown in Figure 2, but the exact causal pathway by which this is achieved is not yet clear.

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References


